Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

Climate Prediction Working Group

First BOG Session, 21-May-2019

Agenda

1. Summary of current activities by each group

    i. SMHI (Ralf) ongoing decadal prediction work & plans
    ii. DMI (Shuting) anomaly initialized predictions & sensitivity tests
    iii. CNR (Danila) testing some innovative initialization methods (MsC)
    iv. BSC (Pablo) preliminary results from DCPP component A
    v. Others?

2. Synthesis of initialization methods, experiments & scientific interests

3. Discussion of potential joint analyses/synergies

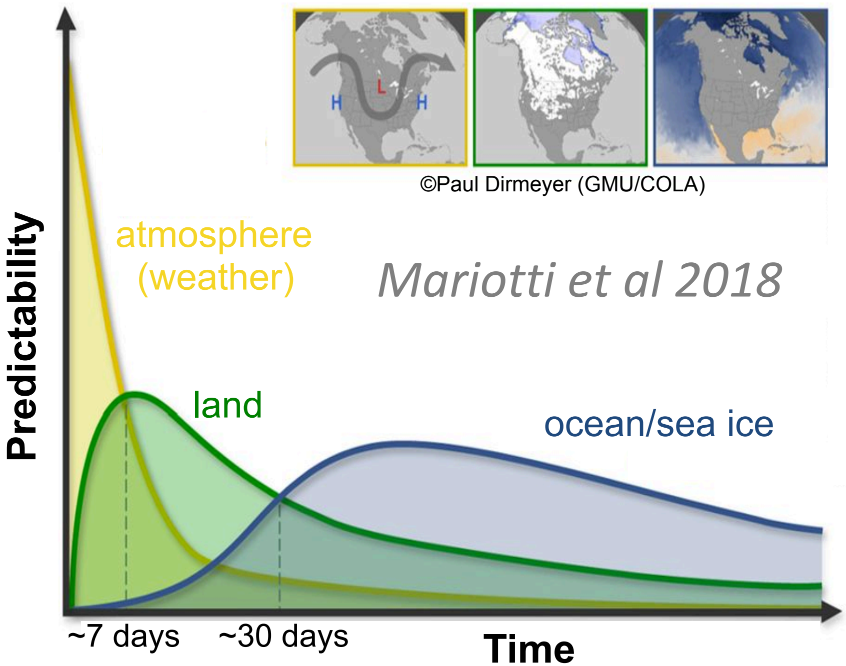
4. AOB

2. Summary of current activities by each group

i. SMHI (Ralf) ongoing decadal prediction work & plans
ii. DMI (Shutting) anomaly initialized predictions & sensitivity tests
iii. CNR (Danila) testing some innovative initialization methods (MsC)
iv. BSC (Pablo) preliminary results from DCPP component A
v. Others?

Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

Internal sources of Climate Predictability



Climate prediction — time horizon → **Weeks Decades**

It relies on the longer memory of ther elements of the climate system

ocean

sea ice

soil moisture

Preliminary results from DCPP Component A

Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

Initial Conditions

ATM:
Interpolated to model grid with OpenIFS (now performed locally at BSC)

Atmosphere reanalysis **(ERA 40 + Interim)**

Land reanalysis **(ERA-Land)**

Ocean reanalysis **(ORAS4)**

Sea Ice reanalysis

produced in-house

LAND:
Offline land-surface simulation with near-surface meteorology and corrected fluxes from ERA-Interim

By Emanuel Dutra

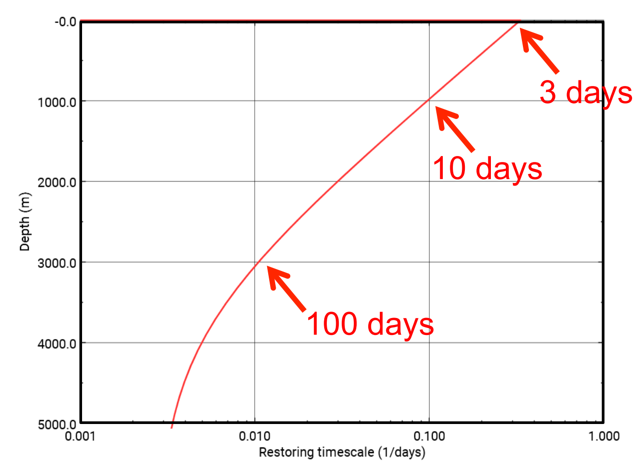
OCE+ SI:
Historical reconstruction with NEMO-LIM stand alone, forced with ERA-40/Interim fluxes, and nudged globally towards 3D T and S from ORAS4

Default surface restoring coefficients

γ_T = -40W/m²/K

γ_S = -150 kg/m2/s/psu

Default 3D restoring timescales



Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

DCPP Component A Protocol

Final Forecast system

- Full-field initialized every year from 1960-2018
- 10 ensemble members per start-date
- Forecast horizon of 11 years

Current Status/Preliminary analysis

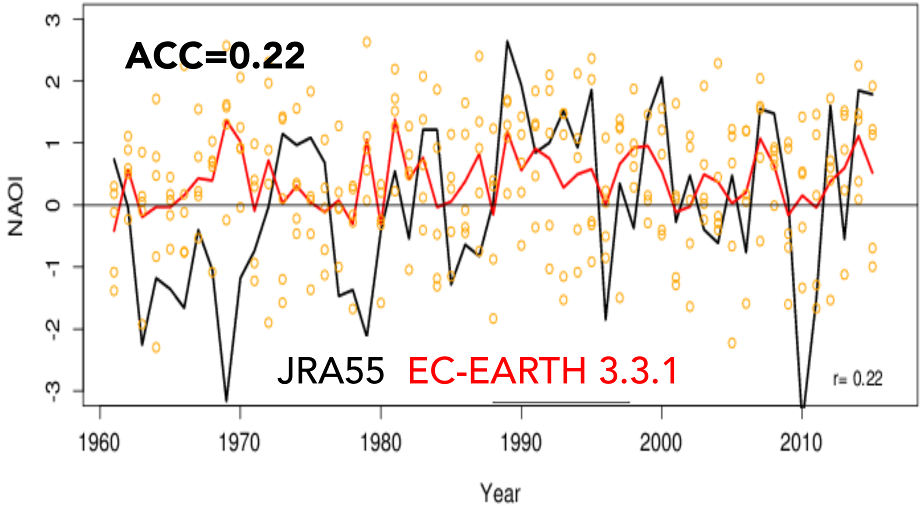
- Initialized every year from 1960-**2014**
- **5** ensemble members per start-date
- Forecast horizon of **5** years

Predictability of atmospheric variables

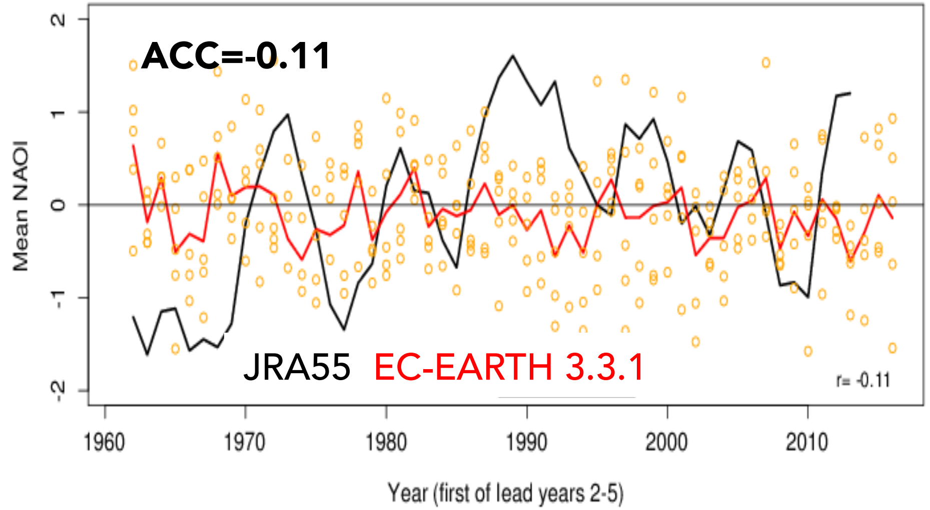
NAO-Index as defined in Jianping & Wang (2003):

35°N-65°N difference of standardised zonally averaged winter MSLP anomalies in the longitudinal band **80°W-40°E**

NAO DJF **Year 1** (forecast months 2-4)



NAO DJF **Years 2-5**



Unlike in other prediction systems, no significant skill in the NAO is obtained

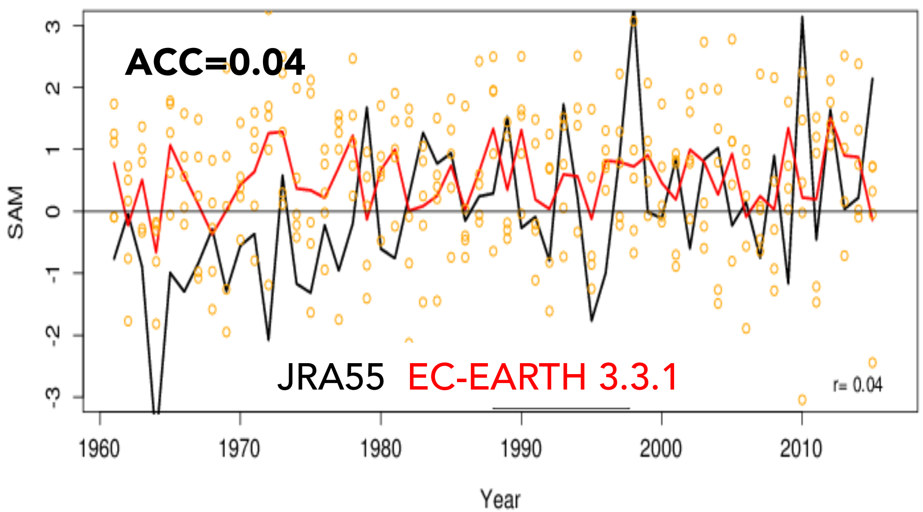
Larger ensemble sizes might be needed to detect the predictable NAO component

Predictability of atmospheric variables

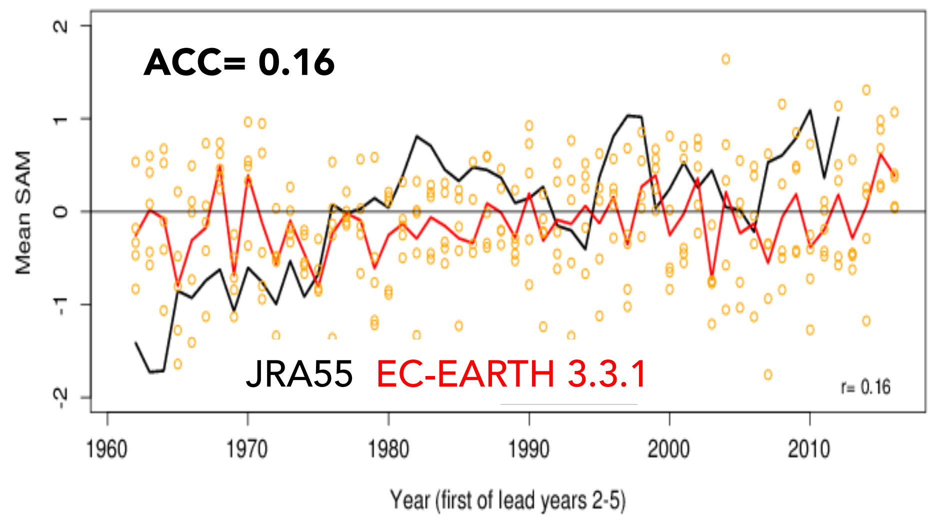
SAM-Index as defined in Gong & Wang (1999):

40°S-65°S difference of standardised zonally averaged winter MSLP anomalies

SAM JJA **Year 1** (forecast months 8-10)



SAM JJA **Years 2-5**

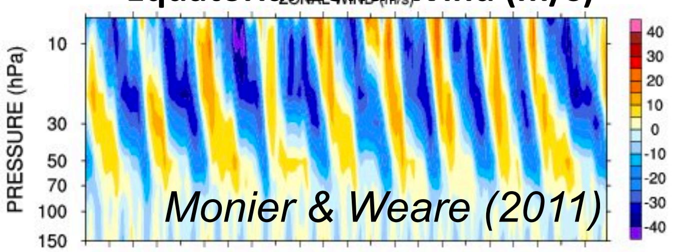


Same results as for the NAO are obtained for the winter SAM

Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

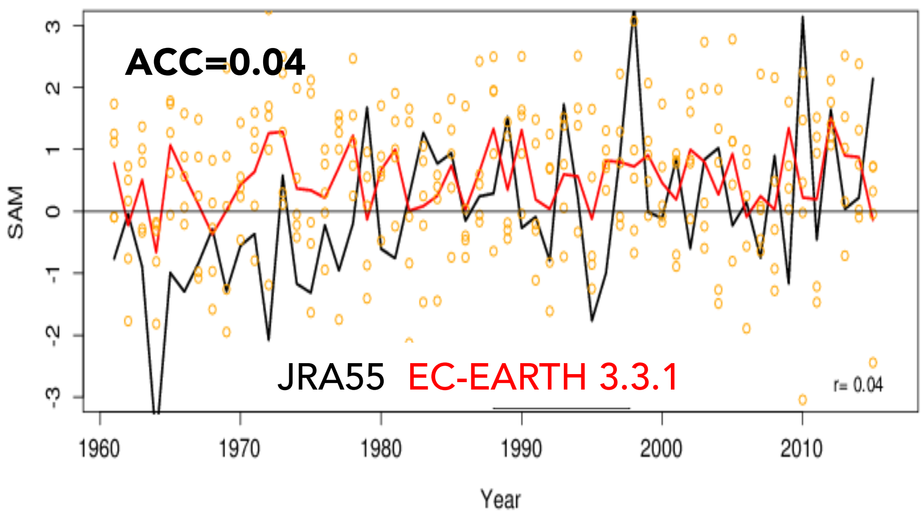
Predictability of atmospheric variables

QBO-Index as defined in···

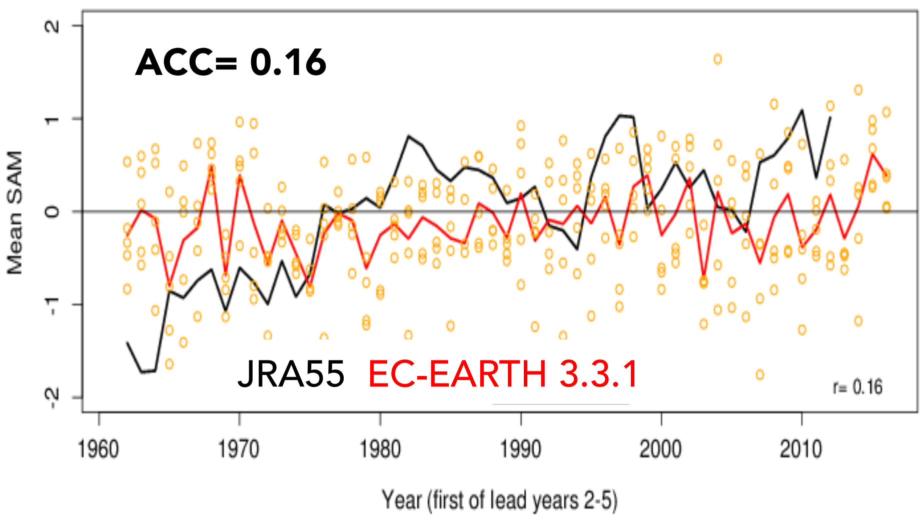


40°S-65°S difference of standardised zonally averaged winter MSLP anomalies

SAM JJA **Year 1** (forecast months 8-10)



SAM JJA **Years 2-5**



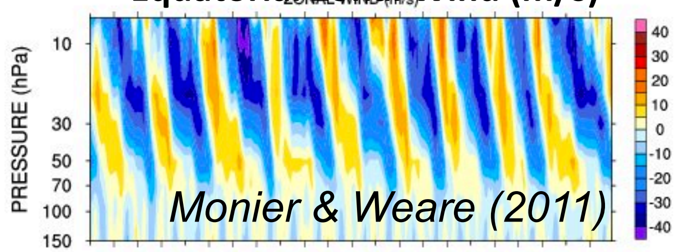
The QBO seems to be highly predictable in the first forecast year

Predictability of atmospheric variables

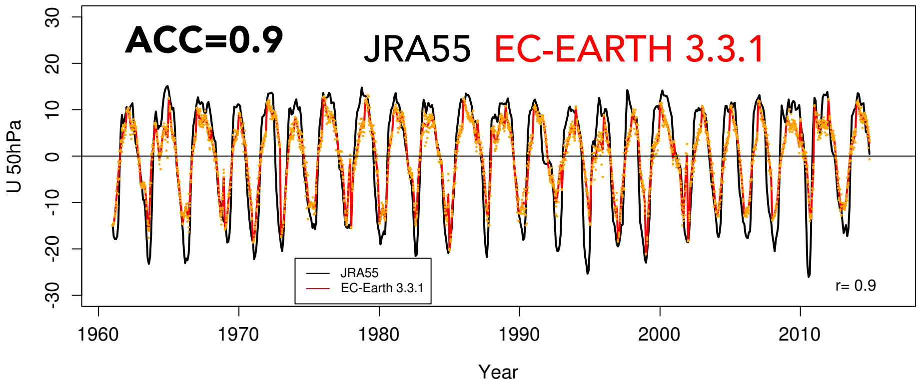
QBO-Index defined as the zonally averaged zonal wind at the **Equator and 50hPa**

Anomalies are computed with respect to the seasonal mean (as a function of lead time)

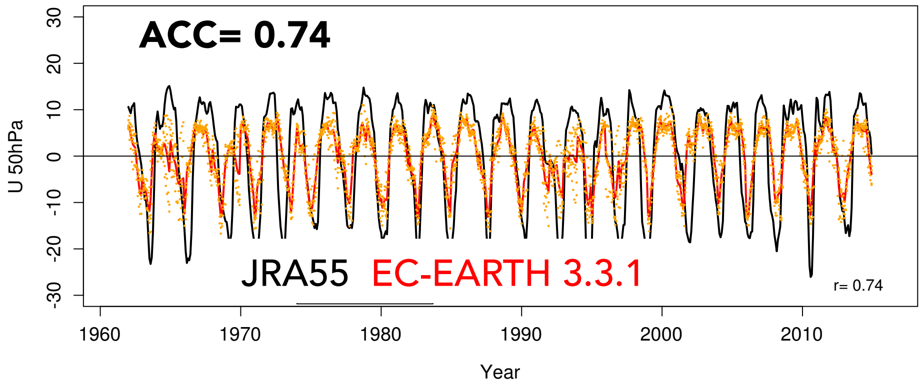
Equatorial Zonal Wind (m/s)



QBO in forecast year 1 (months 1-12)



QBO in forecast year 2



The QBO seems to be highly predictable in the first and second forecast years

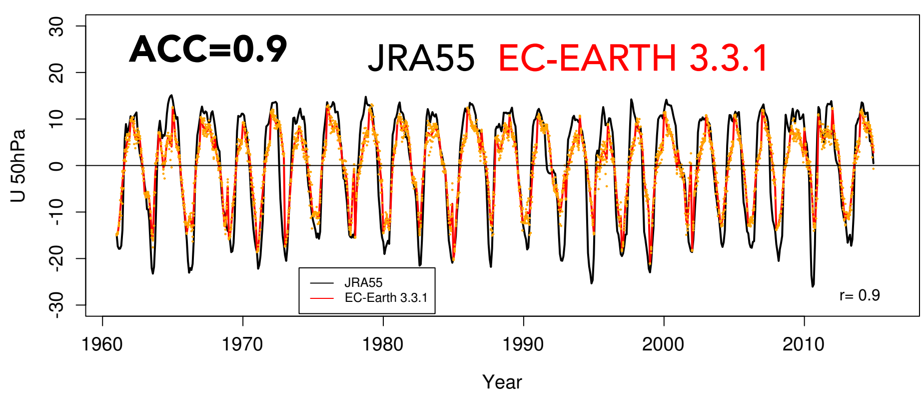
This skill is unrelated to the effect of the seasonal cycle

Predictability of atmospheric variables

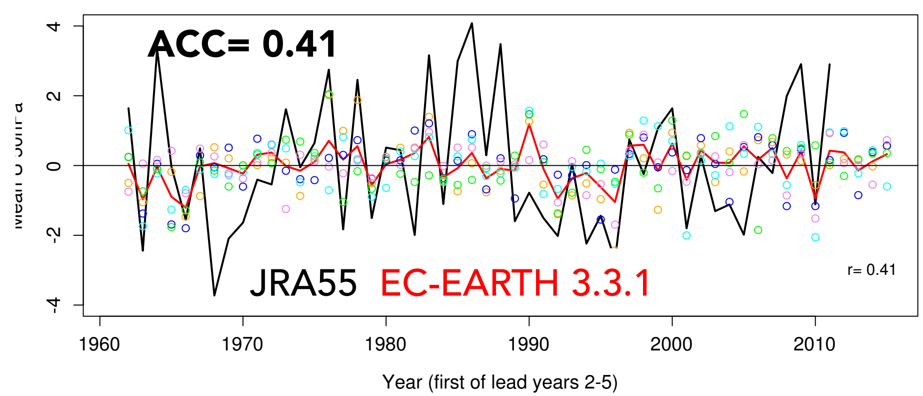
QBO-Index defined as the zonally averaged zonal wind at the **Equator and 50hPa**

Anomalies are computed with respect to the seasonal mean (as a function of lead time)

QBO in forecast year 1 (months 1-12)



QBO in forecast years 2-5



The QBO seems to be partly predictable from the second to fifth forecast years

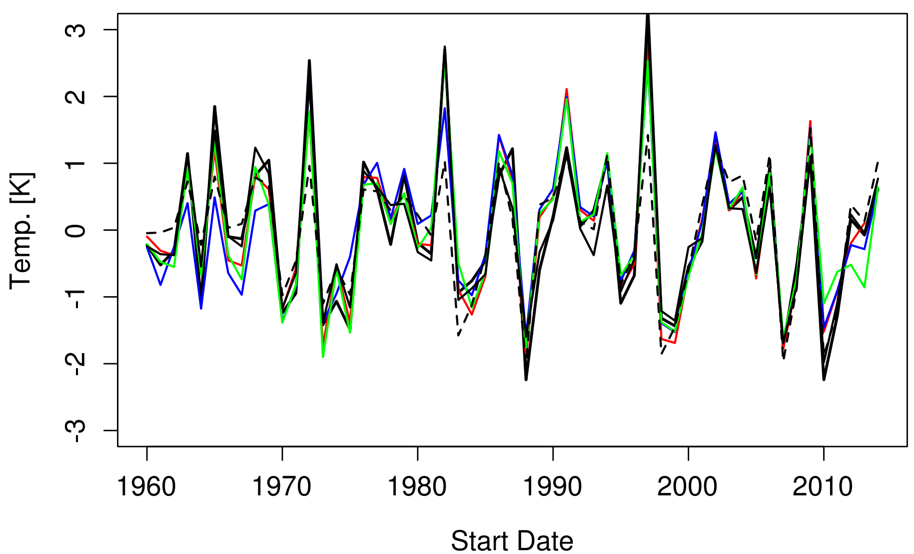
Skill is unrelated to the seasonal cycle, and is a consequence of its strong periodicity

Predictability of ocean variables

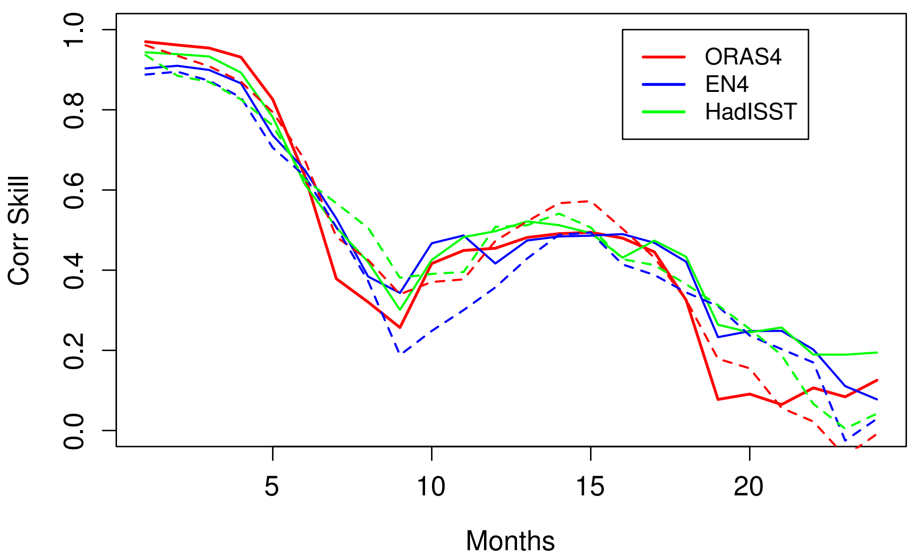
ENSO-Index: Niño3.4

Regional average of SST anomalies in the box **[5°N-5°S, 170°W-120°W]**

Observed and Forecasted Niño3.4



Niño3.4 Anomaly Correlation Coefficient

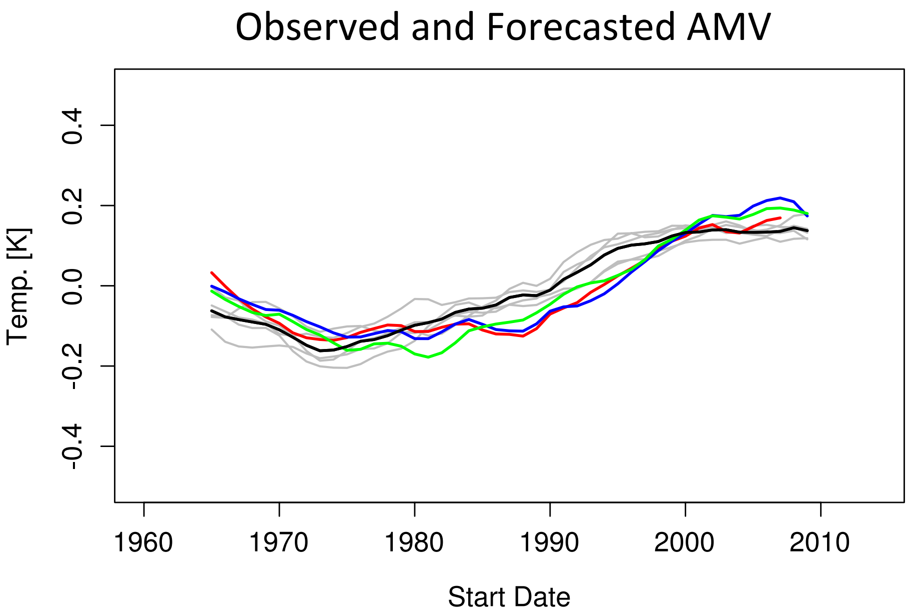


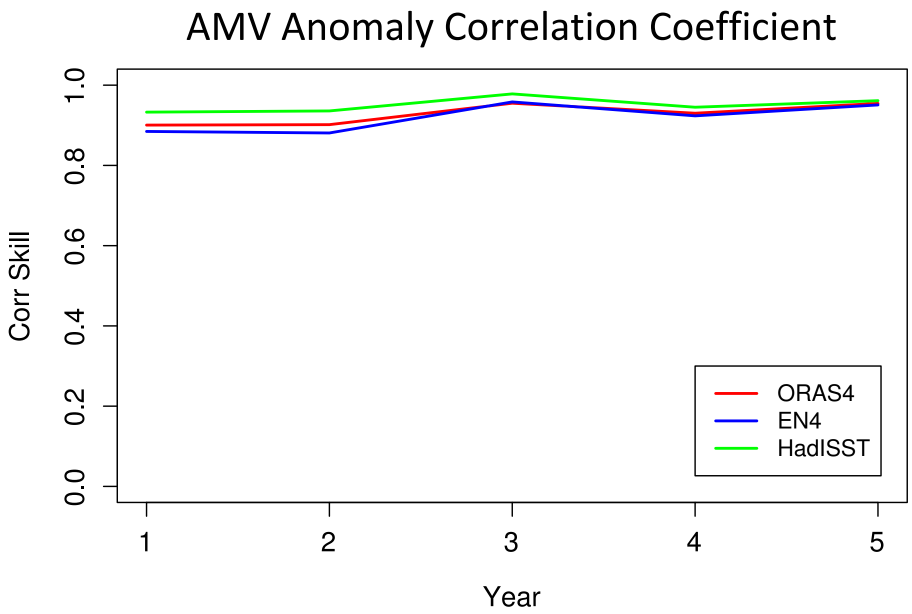
The hindcast maintains high ENSO skill during the first 5 forecast months (DEC through APR), and experiences some skill reemergence in the second winter

Predictability of ocean variables

AMV-Index as defined in Trenberth & Shea (2006):

Decadally smoothed difference between the SST average in the **North Atlantic [0-60°N, 80°W-0]** and the **global mean SST**





The models has really high AMV skill, at least for the first 5 forecast years

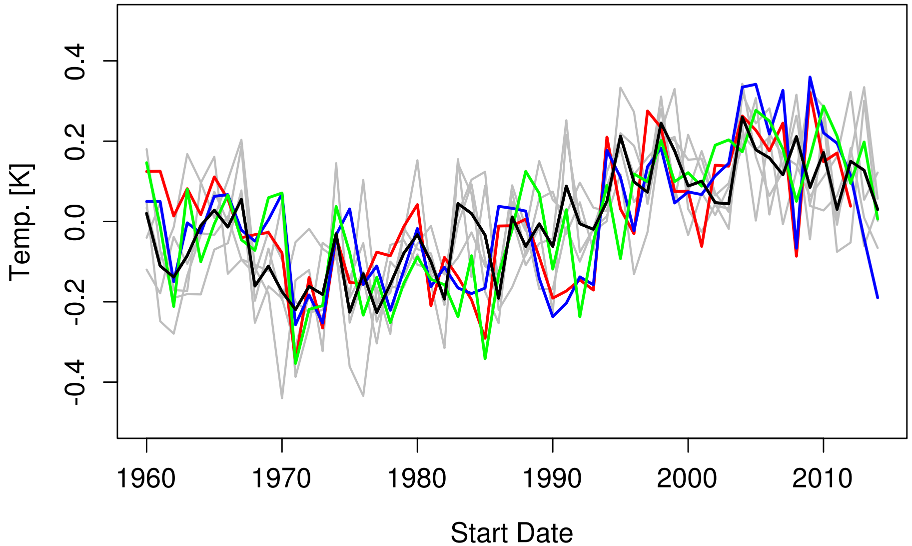
It might be due to the reduced degrees of freedom as a result of the smoothing

Predictability of ocean variables

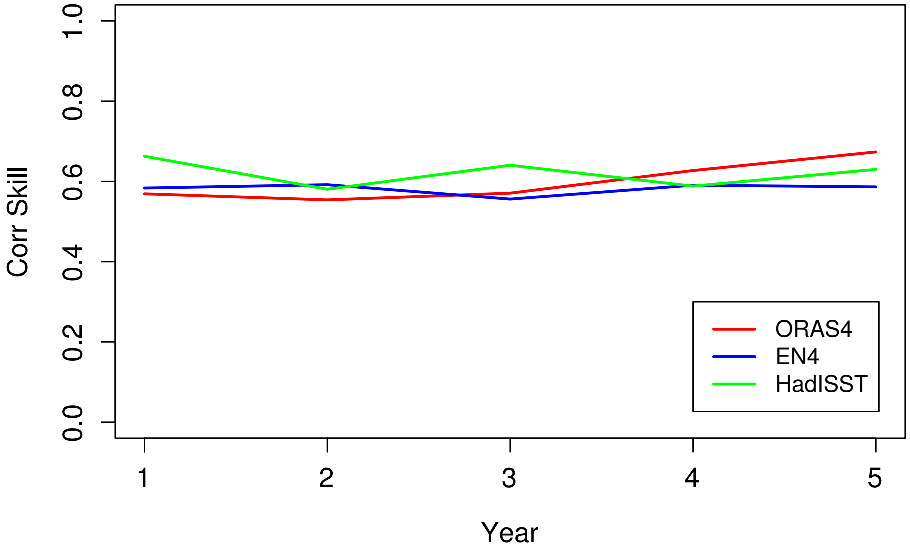
AMV-Index as defined in Trenberth & Shea (2006):

Raw difference between the SST average in the **North Atlantic [0-60°N, 80°W-0]** and the **global mean SST**

Observed and Forecasted AMV



AMV Anomaly Correlation Coefficient



The skill drops but remains high also for the unfiltered timeseries

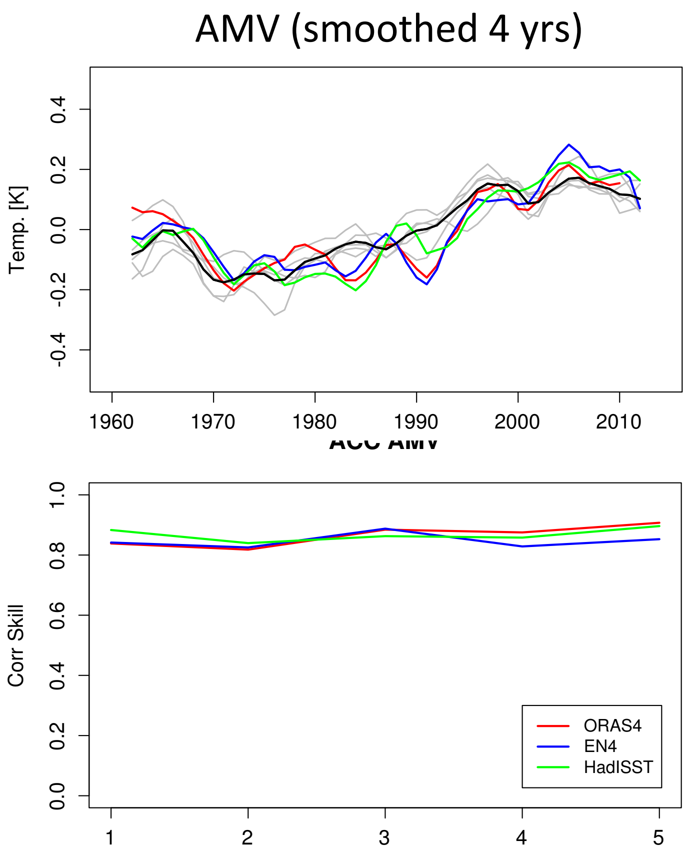
Barcelona Supercomputing Center
Centro Nacional de Supercomputación

EXCELENCIA SEVERO OCHOA

Predictability of ocean variables

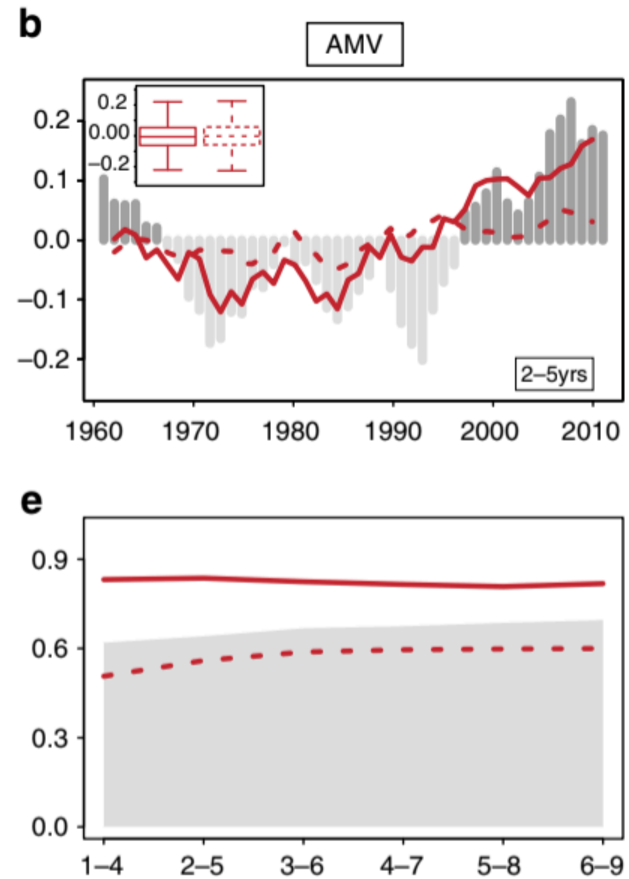
AMV (smoothed with 4yr running means)

How does it compare with other systems?



Doblas-Reyes et al (2013)

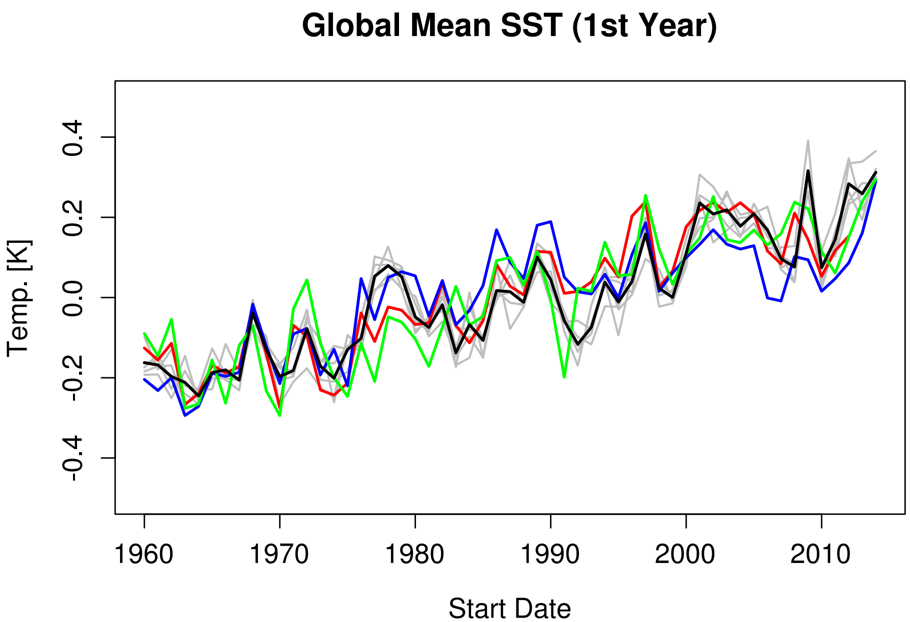
Multi-model CMIP5 skill

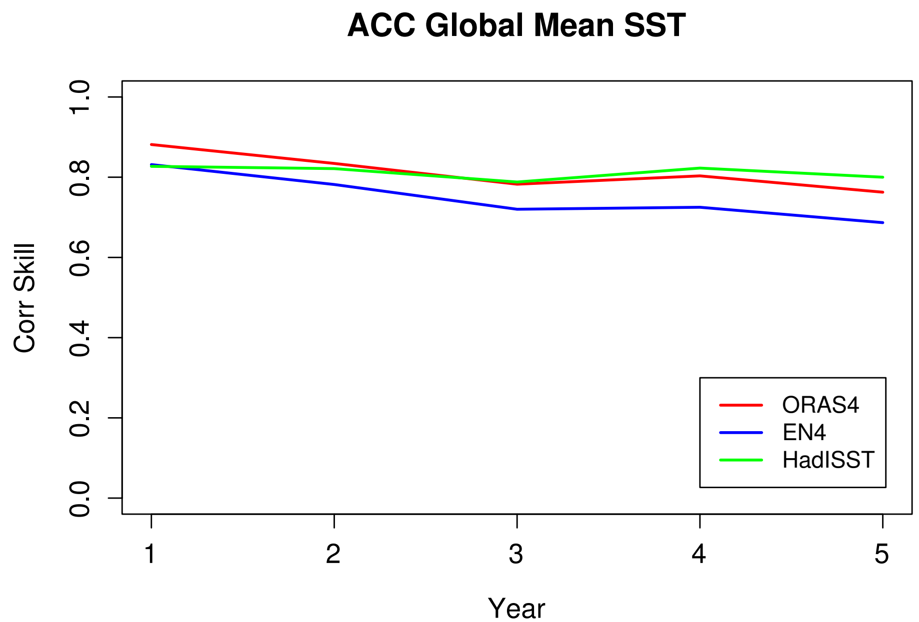


Our skill is at the very least comparable to that of the CMIP5 ensemble

Predictability of ocean variables

Global Mean SST

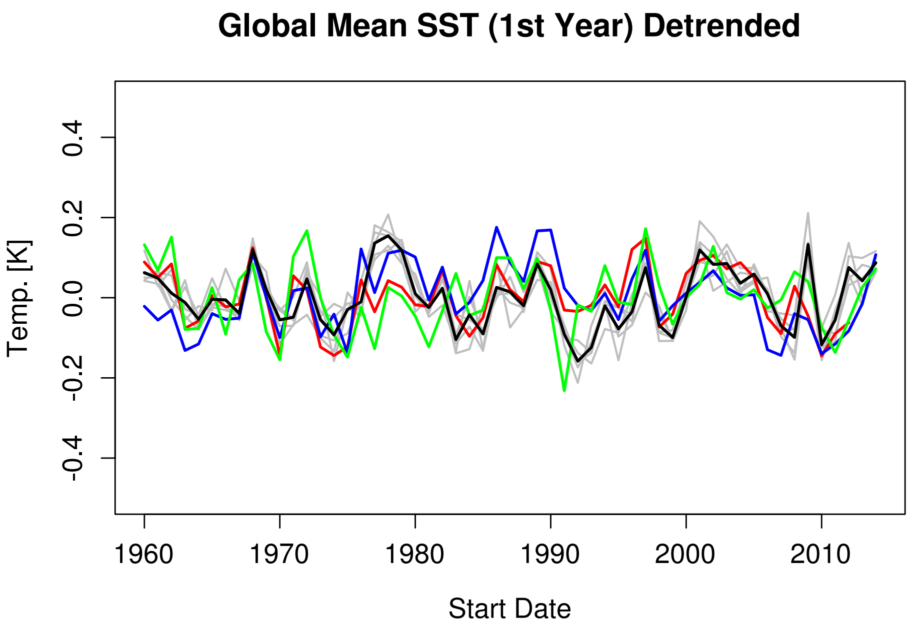


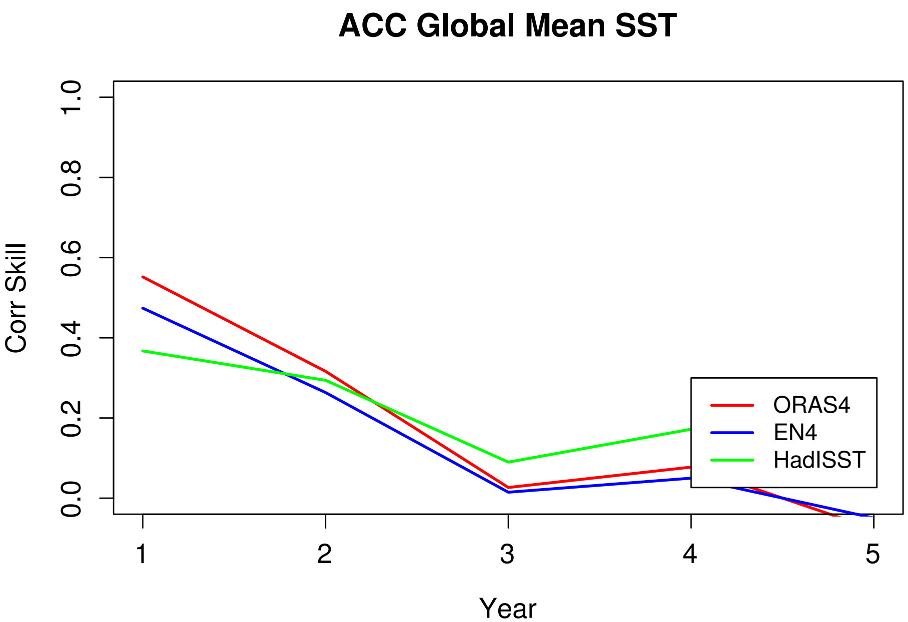


Global mean temperature is also largely predictable, although a non-negligible contribution comes from the long-term trend.

Predictability of ocean variables

Global Mean SST





After a linear detrending (which is a rather artificial approach) the skill of global mean temperature goes down substantially, especially after the 2nd forecast year

A comparison with the non-initialized forecasts would be the right way to identify the skill that arises from internal variability sources

Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

Next to be done:

1. **Finalising the preliminary analysis:**
   - Spatial ACC maps for surface temperature, SLP and precipitation
   - Comparing with DCPP in old CMIP5 version
   - Comparing with the non-initialized forecasts (historical+ssp245)

   Lingering question*: Is our historical ensemble a reliable reference to estimate the added-value of initialization?*

2. **Completing the DCPP experimental setup**

3. **Exploring the benefits of other nudging approaches in seasonal forecast mode**

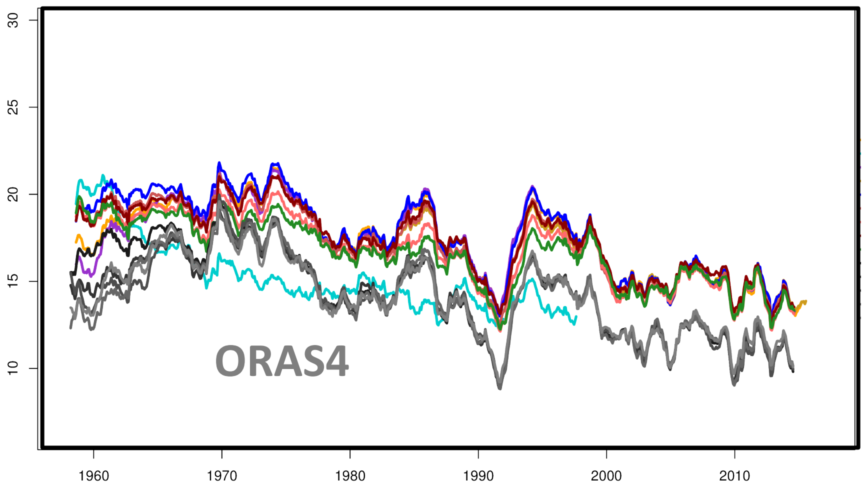
   Ultimate goal: *fully coupled assimilation reconstruction of atmosphere, ocean and sea ice)*

Testing the nudging strength for initialization

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

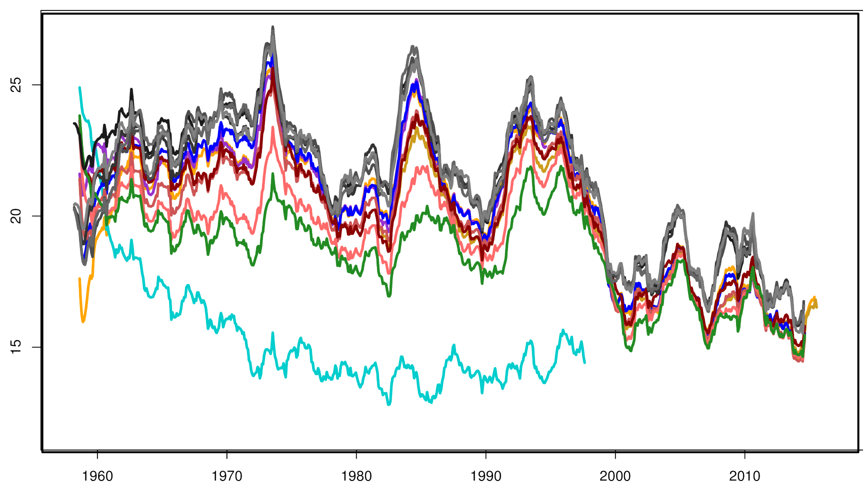
EXCELENCIA SEVERO OCHOA

AMOC evolution at 26N

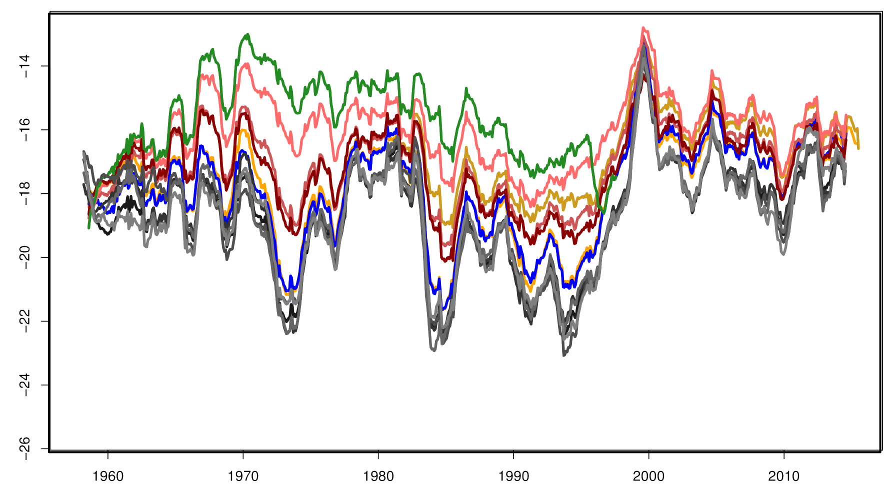


EXP	Surface	3D nudging
a1e1/a1ue	Standard	Standard (STD)
a1ga	Standard	No nudging
a1qw	STD x 15	STD
a1u6	Standard	STD x 5(T)- x 10(S)
a1w6	Standard	STD X 3.3
a1w7	Standard	STD x 10
a1wa	Standard	Step function (**a1w7**)
a1x7	Standard	STD x 20

AMOC evolution at 45N



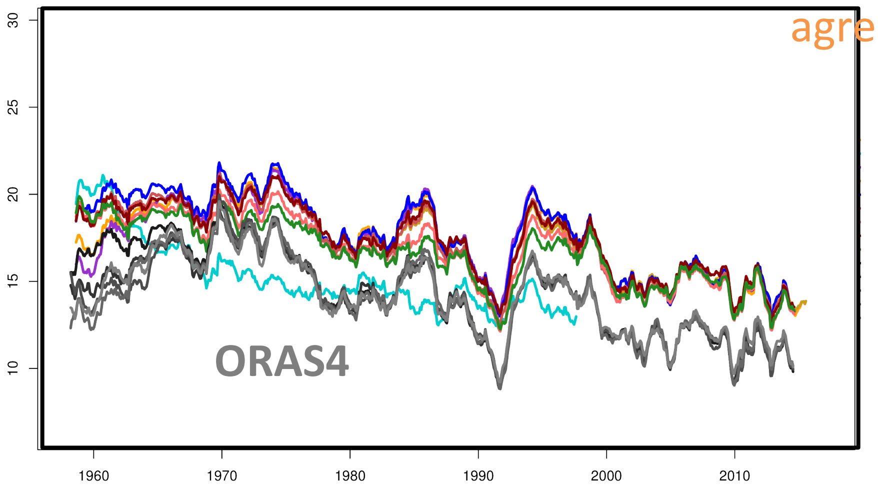
Subpolar gyre strength evolution



The AMOC tends to be underestimated/overestimated wrt ORAS4 at 26N/45N

Testing the nudging strength for initialization

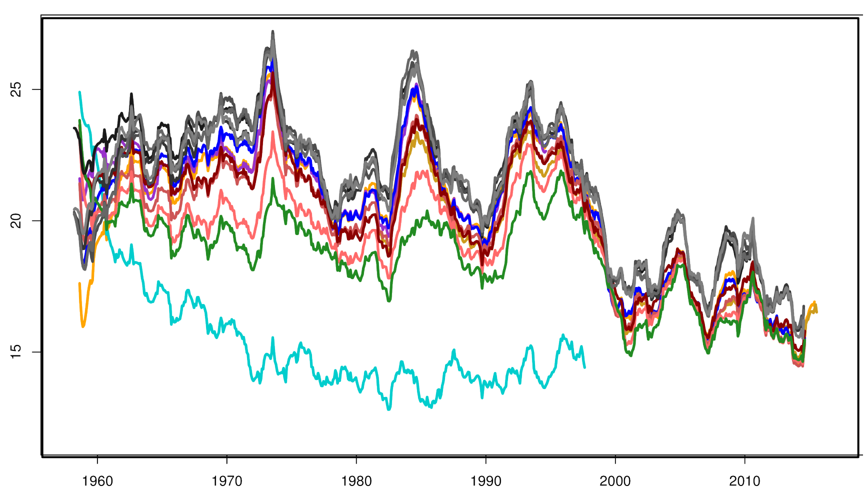
AMOC evolution at 26N



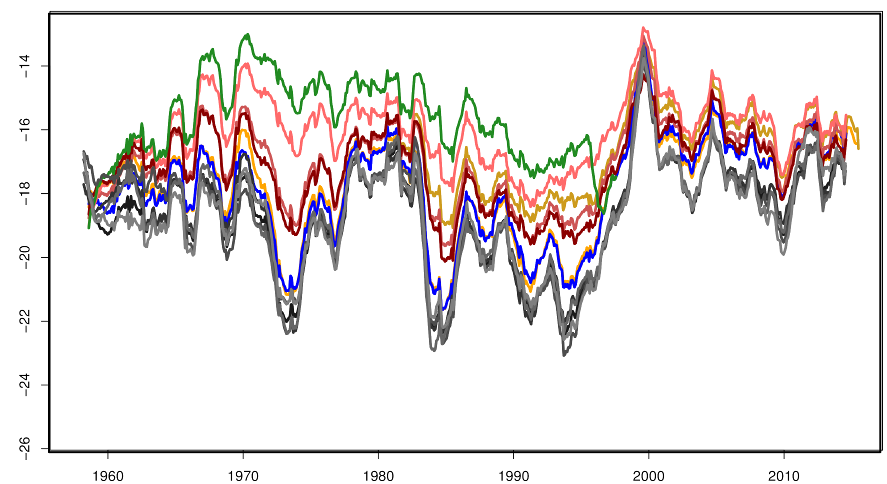
Best overall agreement with ORAS4

EXP	Surface	3D nudging
a1e1/**a1ue**	Standard	Standard (STD)
a1ga	Standard	No nudging
a1qw	STD x 15	STD
a1u6	Standard	STD x 5(T)- x 10(S)
a1w6	Standard	STD X 3.3
a1w7	Standard	STD x 10
a1wa	Standard	Step function (**a1w7**)
a1x7	Standard	STD x 20

AMOC evolution at 45N



Subpolar gyre strength evolution

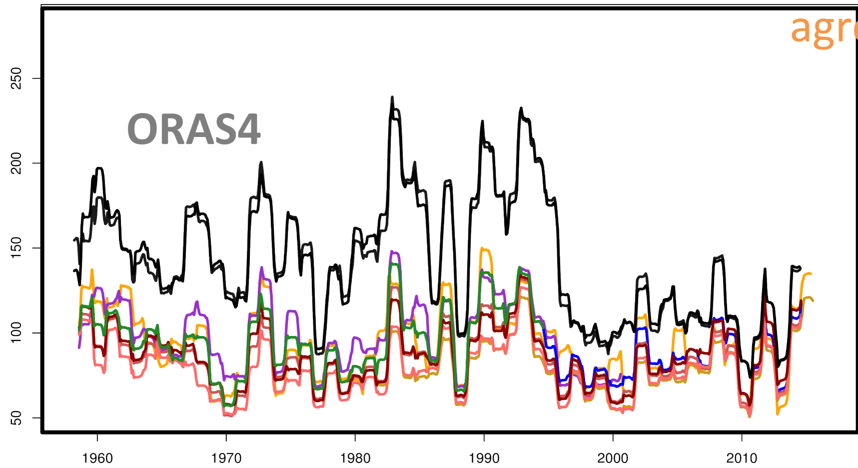


The AMOC tends to be underestimated/overestimated wrt ORAS4 at 26N/45N

Testing the nudging strength for initialization

Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

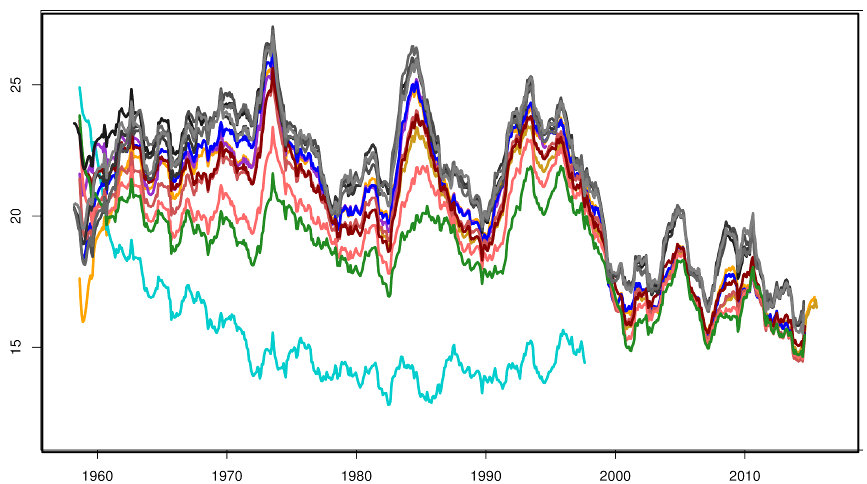
Labrador Mixed Layer Depth



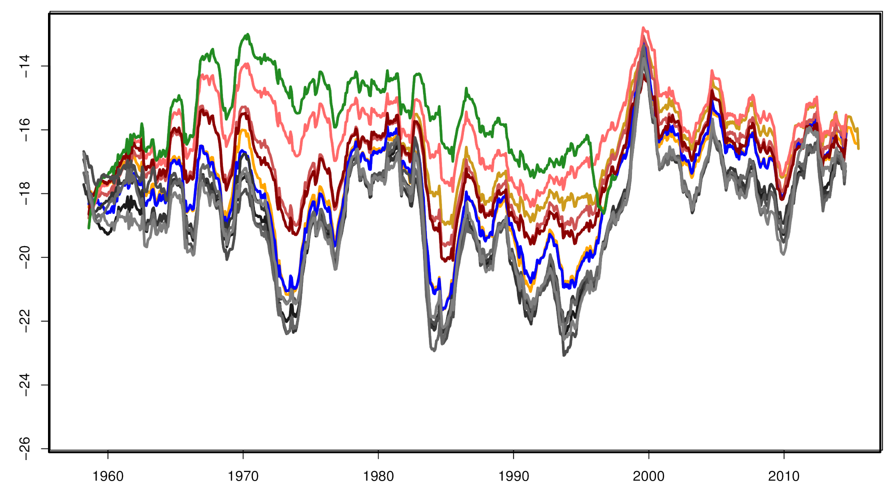
Best overall agreement with ORAS4

EXP	Surface	3D nudging
a1e1/**a1ue**	Standard	Standard (STD)
a1ga	Standard	No nudging
a1qw	STD x 15	STD
a1u6	Standard	STD x 5(T)- x 10(S)
a1w6	Standard	STD X 3.3
a1w7	Standard	STD x 10
a1wa	Standard	Step function (**a1w7**)
a1x7	Standard	STD x 20

AMOC evolution at 45N



Subpolar gyre strength evolution



The AMOC tends to be underestimated/overestimated wrt ORAS4 at 26N/45N